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Research Article

Implementation of a Kalman Filter for Noise Reduction on the INA219 Current Sensor

Achmad Marzuki*, Taufik Muzakkir, Muhammad Sulkhan Arief

Department of Electrical Engineering, Pontianak State Polytechnic, Pontianak, Indonesia

Abstract

The existence of a sensor is very essential and is needed by a digital system to produce the right decision. But every use of a sensor will have an error and noise process that cannot be avoided, and greatly affects the accuracy of the measurement results. One of the popular sensors in the market place is the INA219 sensor made by Texas Instrument which is often used to measure dc current. But the results of the experiment show that the sensor cannot be used directly because its output is relatively unstable or fluctuates. This paper implements the Standard Kalman Filter to reduce noise on the INA219 sensor to produce more accurate dc current measurements. The experimental results show that the variance value of the KF output is much smaller than the sensor output, so that the Kalman filter algorithm has worked optimally to produce accurate DC current measurements. Besides that, Kalman Filer is also very suitable for use in DC motor control as a dynamic system that implements duty cycle (D) changes in the PWM method on its DC input voltage. The Output of Standard Kalman Filter which has been implemented with the ESP32 are influenced by the values assigned to the noise sensor covariance matrix (R) and process noise covariance (Q). With a value of R=100, for resistive loads the values of Q=0.5, while for inductive load (DC motor), the values of Q=0.05 have effectively reduced the amount of noise to enhance the accuracy and precision in using the INA219 current sensor.

Keywords

Sensor, INA219, Kalman Filter, Esp32, Accuracy, Precision

1. Introduction

The availability of sensors in the market place has grown and developed very rapidly along with the emergence of variations of applications which have also increased. But before deciding to choose a sensor, for example a voltage, current, distance, pressure sensor, and so on, consumers must be careful about several parameters, including accuracy, precision, resolution, environmental factors, response time, and power consumption. Accuracy and precision are greatly influenced by the existence of noise which is inherent to the sensor and is random and undesirable because it is not related to the input signal. To reduce the influence of noise on a sensor, one method that can be chosen is to use the Standard Kalman Filter (KF) algorithm which has the ability to handle noise that changes continuously. KF is a concept that has been around for decades, and is widely used in many applications, and in fact KF is one of the best methods often used for dynamic state [1, 2]. State estimation KF can provide predictions of the state of a system and the associated uncertainties, but

*Corresponding author: mzkachmad@yahoo.com (Achmad Marzuki)

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cannot cope well if the error or noise is systematic in the measurement process [2].

Several applied studies related to the use of KF continue to be developed to produce more accurate parameter measurements. In measuring the spacing of a Tiny parallel capacitor plates, the use of KF has increased accuracy to 99%, namely between 0 mm and 5 mm [3]. In distance estimation measurements using an ultrasonic sensor (HC-SR04), the experimental results show that the use of KF has increased the estimated accuracy value to 7% with optimal values of R =100 and Q = 0.01 [4]. Another application of KF is in measuring distance values in the HOOKE'S LAW PROPS SYSTEM to overcome the problem of fluctuations (unstable sensor output), where the value of R =10 and H =1 has effectively reduced the amount of interference (noise), namely reducing mean squared error (MSE) so that the best performance can reach 89.23% [5]. Another application of the Kalman filter is to reduce noise in the Inertial Measurement Unit (IMU), which consists of an accelerometer sensor and a gyro sensor. The results of this study indicate that noise can be reduced with the KF by changing the values of R=10 and Q=0.1 to produce better accuracy [6]. Another implementation of RSSI-based distance measurement in LORA-based communication networks, the experimental results show that the distance from the path created by RSSI using Kalman filter is very close to the actual distance. The error generated by using KF is 5%, while without KF it has an error of 22.9%. [7]. Kalman filter is also used to minimize the error deviation rates of GPS data from NOVATEL and UBLOX base vehicle tracking device. As a result of this study, it was observed that Kalman Filter gave a good result on location data which has a noisy data type [8]. In the field of smart irrigation agricultural irrigation that requires reading of soil temperature and moisture parameters sent wirelessly with a network of sensors spread across several locations, with wireless data collection or so-called wireless sensor net-work (WSN) will face various significant challenges. By combining the Autoregressive model and Kalman filter has become a very effective method for detecting sensor faults used in a Smart irrigation [9]. Kalman Filter has also been used for temperature reading of MAX667 sensor to improve the accuracy of temperature reading [10]. Nowadays, smart sensors have developed into complex applications to handle various measurements. To produce better estimates of sensor readings, Kalman filters can be used in more complex models with very efficient use of CPU computation, even with low-power microcontrollers. [11].

Another approach is the use of Extended Kalman Filter for state estimation in WDS (Water distribution system) water distribution system to identify the presence of damaged sensors to reduce the negative impact of incorrect measurements on operational decisions [12]. The use of the Kalman Filter can also reduce or minimize oscillating signals into more stable and reliable output values when using the AC712 type current sensor to improve its level of accuracy [13, 14]. The integration of the Kalman Filter and PI controller with the Firebase Realtime Database can improve the accuracy of temperature monitoring in fish ponds and has positive implications for increasing efficiency and fish welfare [15]. The use of an Unscented Kalman Filter (UKF) in an RSSI-based distance localization system can also reduce noise and variance in the RSSI. The UKF is also the most optimal algorithm for Wi-Fi tracking systems (Wi-Fi trackers) [16]. In the field of DC-DC converters, especially the Buck converter type, the Kalman Filter can be used to estimate state variables (State Variable) on inductor current and capacitor voltage in a noisy and noiseless environment. In this model, the covariance matrix is defined and determined so that Q < R [17]. The use of KF on moving objects in real-time situations has been successfully applied [18], and it also was confirmed that FPGA Implementation for object tracking with hardware based Kalman filter hardware is suitable for real-time processing [19]. The use of KF in the transportation sector is how to monitor fuel levels in motor vehicles due to uneven (bumpy) roads that cause shaking in the fuel tank. The filtering process is carried out by changing the process error covariance (Q) and measurement error (R) in the Kalman filter. In this study, fuel sensor noise is simulated using a Tank Simulator controlled by an actuator so that it causes a movement that can be tilted towards the x-axis and y-axis to resemble vehicle behavior. The results of this study produce an average error of 4.73% or smaller than without a filter, which is 6.65% [20].

Based on the research mentioned above, it is crucial to assist sensor applicators (customers), particularly in the use of the INA219 DC current sensor, whose output still contains noise that can cause unstable measurements. This re-search will focus on implementing a Standard Kalman Filter (KF) to significantly reduce noises for accuracy and precision measurements.

2. Materials and Methods

In this study, testing will be carried out on the system to obtain DC current parameters as sensor and KF output to determine the system response and noise reduction to produce higher accuracy and precision measurements.

2.1. Material

The core components in this experiment are INA219 current sensors and an ESP32 Microcontroller which functions to implement the Standard Kalman Filter algorithm.

2.1.1. INA219 Sensor

The INA219 is a high-side current shunt and power monitor with an I^2C interface as shown in the Figure 1. The INA219 monitors both shunt drop and supply voltage, with programmable conversion times and filtering. A programmable calibration value, combined with an internal multiplier, enables direct readouts in amperes. An additional multiplying register calculates power in watts. The I^2C interface features 16 programmable addresses. The INA219 senses across shunts on buses that can vary from 0V to 26V. The device uses a single +3V to +5.5V supply, drawing a maximum of 1mA of supply current and can operates from–40 ℃ to +125 ℃.

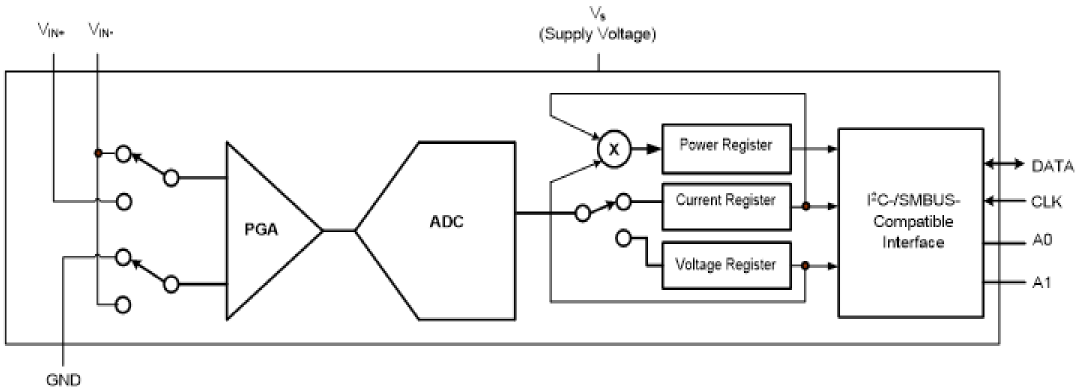
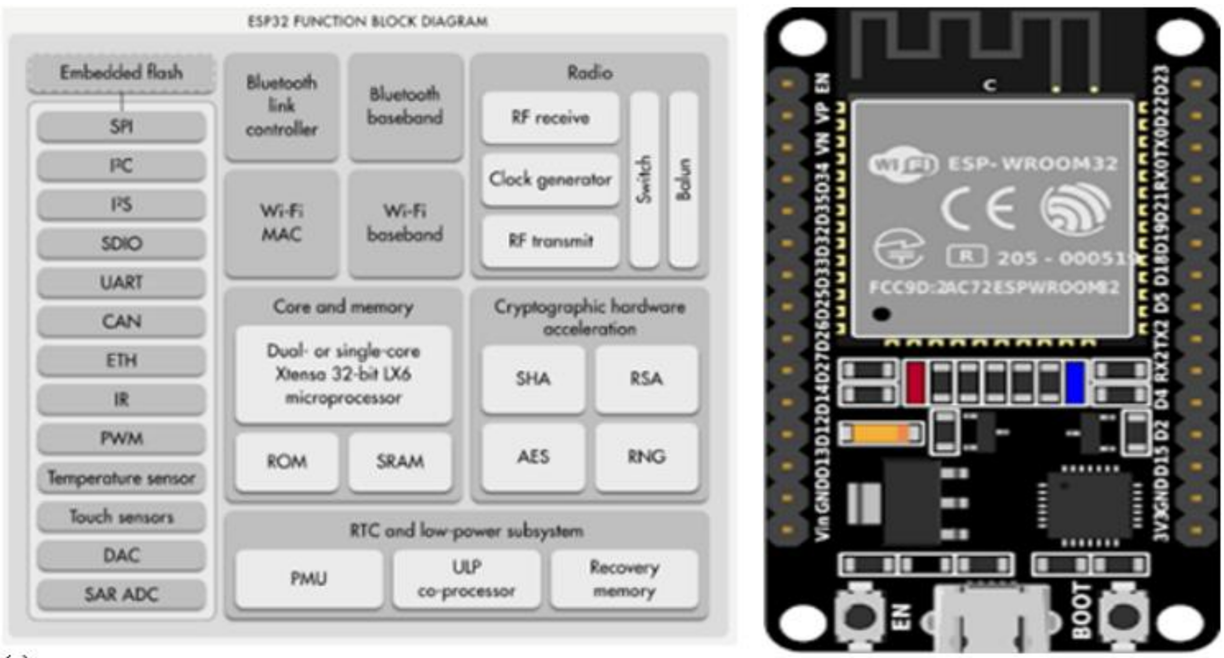


Figure 1. Simplified Schematic of INA219.

2.1.2. Esp32 Microcontroller

The ESP32 was developed by Espressif Systems and uses a dual-core or single-core Tensilica Xtensa LX6 microprocessor with a clock rate of up to 240 MHZ as shown in Figure 2. and power management modules. The ESP32 module is the successor to the ESP8266 module which is quite popular for IoT applications, has been supported with faster Wi-Fi facilities, more GPIOs, and supports Bluetooth Low Energy.

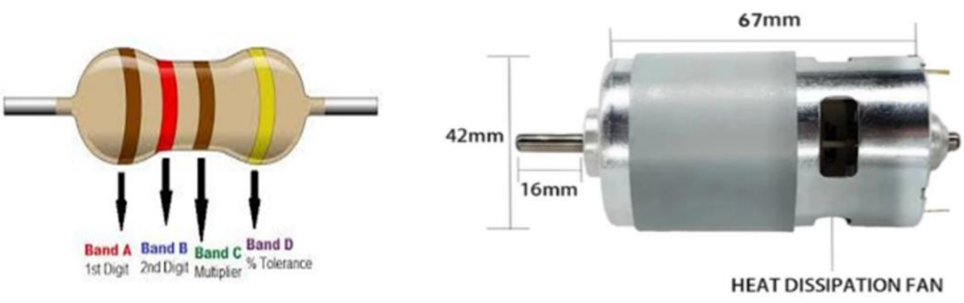


(a) (b)

Figure 2. (a) ESP32 Functional Block Diagram; (b) Top view of ESP32.

2.1.3. Experimental Loads

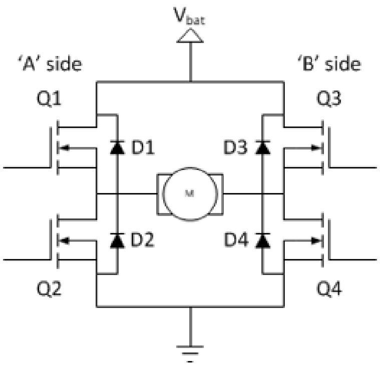
The loads used in this experiment are several carbon resistors with four colors, and a DC motor with the following specifications: Single bearing, Pmax: 100W, No-load speed: 12000 rpm, No-load current: 1.2A, as shown in Figure 3.



(a) (b)

Figure 3. *(a) Carbon Resistor (b) DC motor.*

In the experiment with a DC motor, the Duty Cycle (D) value will be changed to produce different motor speeds (rpm). The motor speed change is done using an L298N which is a dual H-Bridge motor driver (Figure 4) by sending a PWM signal through one of the GPIOs on the esp32.



(a)

(b)

Figure 4. *(a) H-bridge Circuit; (b) L298N driver board.*

2.2. Methods

The main objective of this study is to present the effectiveness of the Standard Kalman Filter Algorithm to reduce noises when using the INA219 type dc current sensor.

2.2.1. Standard Kalman Filter

The Kalman filter consists of a set of mathematical equations that can estimate the state of a process by minimizing the mean squared error. With the Kalman filter, a process can be estimated in terms of previous, current and future conditions. The Kalman filter estimates a process using feedback control. First, the filter estimates the state of a process at a time, then receives feedback in the form of sensor measurements that usually contain noise. Thus, the Kalman filter equation can be divided into two parts: the time update and the measurement update equation. The time update equation serves to form an estimate of the current state and error covariance to obtain an estimate for the next time step. The measurement update equation serves to incorporate the new measurement into the previous estimate to obtain a better estimate. The time update equation can also be called the predictor equation, while the measurement update equation can also be called the corrector equation. The final estimate is obtained by combining the predictor-corrector algorithm to solve the numerical problem. The Kalman Filter is often carried out in two phases, namely prediction and update, which can be written with the mathematical equations (1)-(5).

Prediction:

$$\hat{x}_{t|t-1} = F_t\ \hat{x}_{t-1|t-1} + B_t\ u_t \tag{1}$$

$$P_{t|t-1} = F_t\ P_{t-1|t-1}\ F_t^T + Q_t \tag{2}$$

Update:

$$\hat{x}_{t|t} = \hat{x}_{t|t-1} + K_t\big(\,y_t - H_t\hat{x}_{t|t-1}\big) \tag{3}$$

$$K_t = P_{t|t-1}\ H_t^T\ (H_t P_{t|t-1} H_t^T + R_t)^{-1} \tag{4}$$

$$P_{t|t} = (1 - K_t H_t) P_{t|t-1} \tag{5}$$

Equations (1) to (5) are a general model of the Standard Kalman Filter system that can be modified according to the needs and complexity of the built system. The KF implementation process will begin with the initialization process by setting the values of R, Q, Pt and ending with updating the error value for the next calculation as shown in the flowchart in Figure 5.

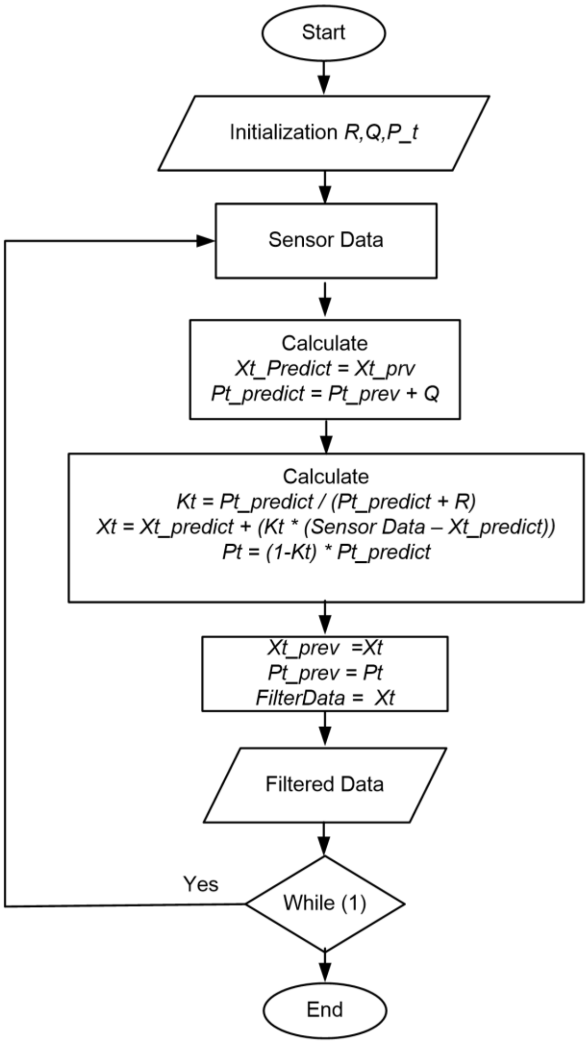


Figure 5. Standard Kalman Filter Algorithm Flowchart [6].

2.2.2. Model Design

The design model in Figure 6 is used for the implementation of KF in the use of INA219 sensors on resistive and inductive loads. In resistive loads, several resistors are used with a tolerance of 5% with a 5 V dc voltage source, while for inductive loads, a 12V/30 watt dc motor is used which is equipped with an L298N driver circuit with a duty cycle (D) setting. Esp32 functions to implement KF in the form of coding (Sketch) using the Arduino IDE 2.3.6 There are two data taken, namely the Sensor and KF output via the ESP32 serial port using the Parallax Data Acquisition tool (PLX-DAQ) software with excel data output which will then be converted into graphical information.

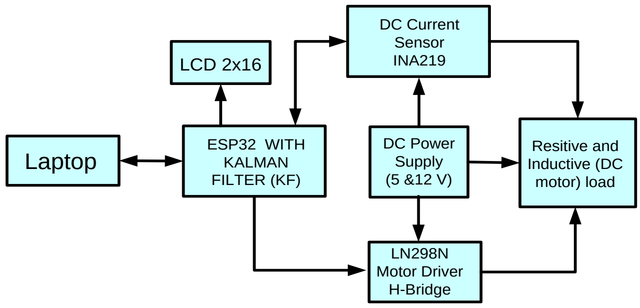


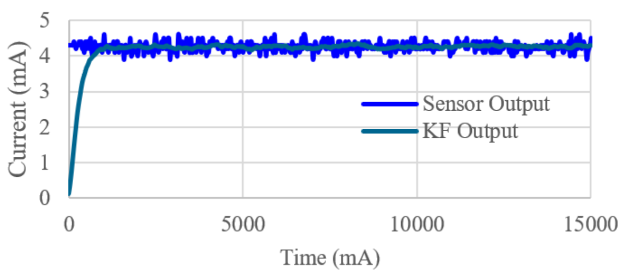
Figure 6. Model design.

3. Results and Discussion

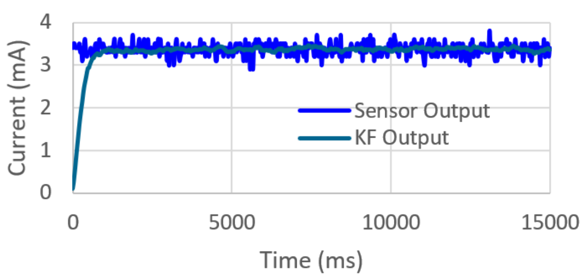
3.1. Resistive Loads

3.1.1. Sensor and KF Output

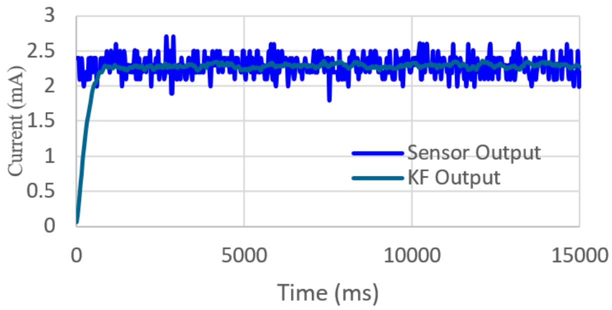
The DC current parameter is taken from the INA219 sensor output, and the current output after going through the Kalman Filter (KF) with covariance R=100 and Q=2. The parameter reading uses a laptop and a PLX-DAQ application so that the current parameters are directly sent to a Microsoft Excel worksheet. The parameter reading uses a sampling time of 30 millisecond and is carried out a thousand times or ends at the reading time of 14970 millisecond, as shown in Figure 7.



(a) R=1200 Ohm



(b) R=1500 Ohm



(c) R=2200 Ohm

Figure 7. Sensor and KF output with resistive load.

On a resistive load with resistor values of 1200, 1500, and 2200 ohms, the first output of the INA219 sensor is still unstable and random. The second output is a dc current after passing through the KF algorithm, which is relatively more stable. This experiment shows that KF has been able to reduce the influence of noise so that the dc current value becomes more stable, and consequently can improve accuracy and precision.

3.1.2. Sensor and KF Output with Disturbance

In this experiment, the loads used are two resistors in parallel, then after the KF output reaches stability, a disturbance is made on the load by removing the load by half. The shape of the change in the sensor output and KF with R = 100 and Q = 2 with this disturbance is shown in Figure 8.

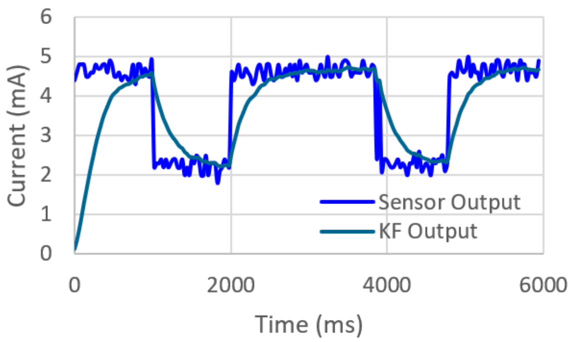


Figure 8. Sensor and KF output on resistive load with disturbance.

Sensor and KF output will change if there is a disturbance in the system. However, the KF output can still respond well to the disturbance, thereby significantly reducing noise and maintaining its stability.

3.1.3. Variance of Sensor and KF Output

The calculation of sensor and KF output variance on resistive loads shown in Table 1 is intended to determine the effectiveness of the Kalman algorithm to improve the accuracy of DC current measurements. With a constant covariance value of R = 100, and Q = 2, the variance value on KF output on several resistive loads is smaller than the sensor output, as shown in Table 1.

Table 1. Sensor and KF output Variances on resistive load.

Resistive load (Ohm)	Sensor Output Variance (mA)	KF Output Variance (mA)
47	0.0259	0.0025
100	0.0161	0.0020
147	0.0216	0.0014
180	0.0163	0.0013
220	0.0188	0.0044
270	0.0190	0.0013
330	0.0184	0.0010
470	0.0164	0.0011
680	0.0164	0.0011
820	0.0225	0.0018
1000	0.0172	0.0012
1200	0.0164	0.0009
1500	0.0192	0.0015
2200	0.0183	0.0011

3.1.4. Sensor and KF with Different Q Values

With a Covariance constant R = 100 and different Q values, namely 2, 6, and 10 respectively, this will affect the KF response towards its stability value, as shown in Figure 9. The larger the Q value used, the faster the KF response towards its stability value and vice versa.

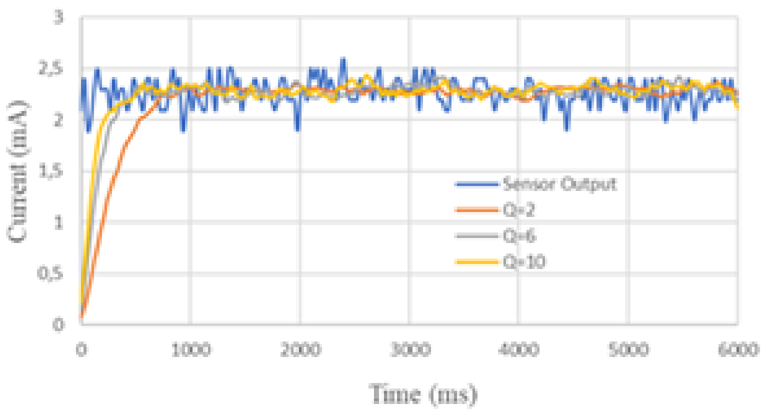


Figure 9. Sensor and KF Output with different Q value.

To produce the smallest variance value on the KF output on a resistive load, the covariance constant Q value is selected using a try and error methodology with the optimal Q value is 0.5 as shown in Table 2.

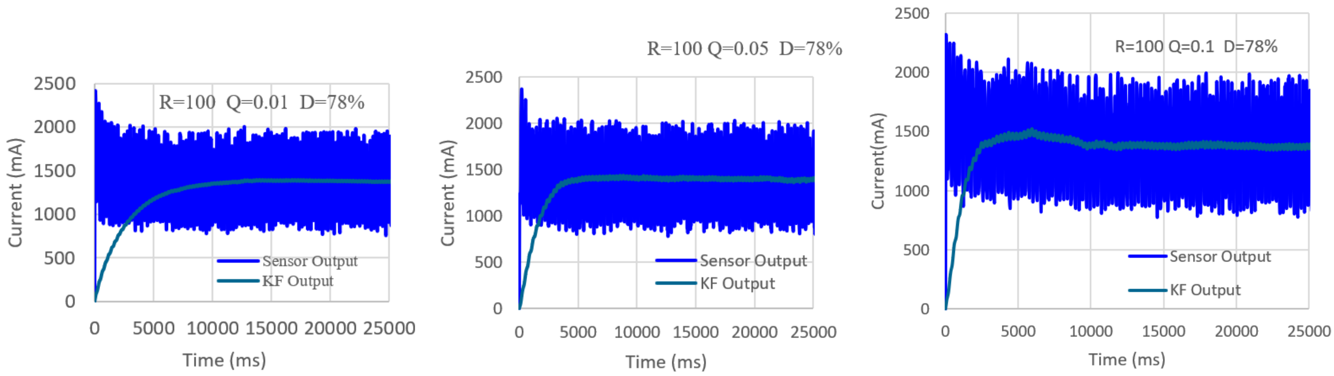
Table 2. Q Constant and KF output Variance on Resistive loads.

Q Constant	KF Output Variance (mA)
0.05	0.0028
0.5	0.0007
1	0.0009
2	0.0013
6	0.0024
10	0.0031

3.2. Inductive Load

3.2.1. Sensor and KF Output

Duty cycle (D) value is the ratio between high level time and period of square wave which can be used to change the input voltage of a DC motor to produce different motor speeds (rpm). If the KF covariance parameter for this DC motor load is R=100 with Q values of 0.01, 0.05, 0.1 respectively and D = 200 (78.43%), and the results are shown in Figure 10.



(a) (b) (c)

Figure 10. Sensor and KF output with different Q value (a) Q=0.01 (b) Q=0.05 (c) Q=0.1.

In this inductive load, disturbance is applied to the DC motor's input supply by providing a PWM value to produce a different duty cycle (D) value. If the D value is increased, the KF output will increase, and vice versa, it will decrease. Although the sensor output value changes over a certain time period, the KF output can still maintain its stability by significantly reducing noise.

3.2.2. Sensor and KF Output with Different Q Values

This experiment aims to determine the change in KF output by giving a value to the Covariance constant R = 100, with the constant Q given differently, namely 0.01, 0.05, and 0.1.

Almost similar to the resistive load, that the smaller the value of the Kalman constant Q, the KF response to reach its stable value requires a longer time and vice versa, as shown in Figure 11.

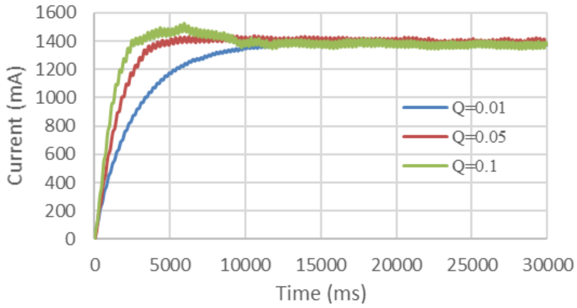


Figure 11. *Sensor and KF Output on different Q value with inductive load.*

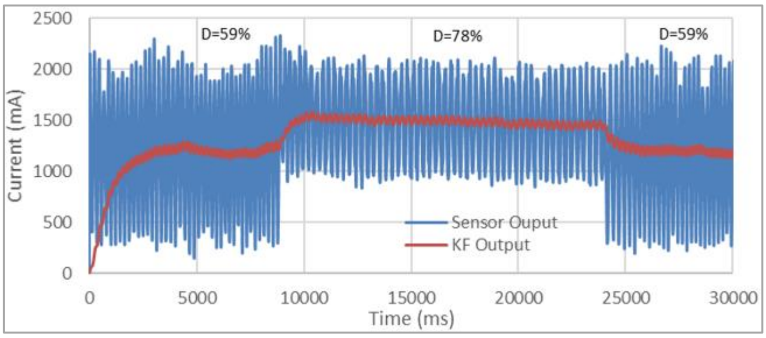
To produce the smallest variance value on the KF output on an inductive load, an experiment was conducted by providing disturbance to the DC motor input with Duty Cycle D=200. The selection of the covariance constant value Q using the try and error methodology resulted in an optimal Q value of 0.05 as shown in Table 3.

Table 3. *KF Output variance at different Q on inductive load.*

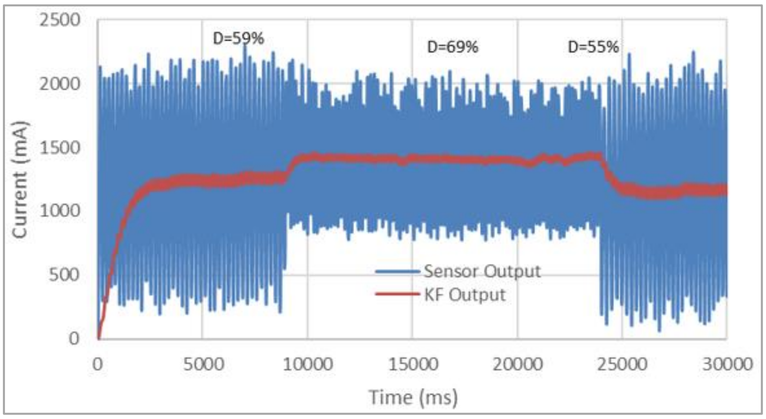
Q Constant	KF Output Variance (mA)
0.01	0.00108
0.05	0.00024
0.1	0.00096
0.2	0.00064
0.4	0.00158

3.2.3. Sensor and KF Output with Different Duty Cycle (D) Value

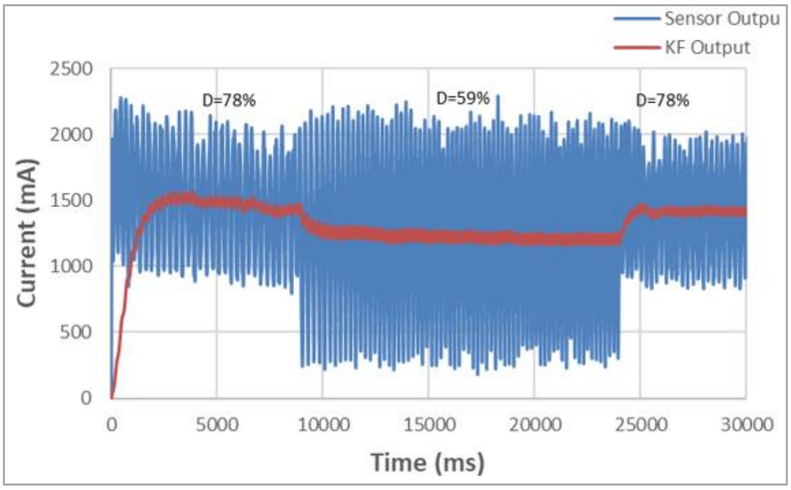
This experiment aims to determine the effect of changing the D value on the KF output with a DC motor load. At different D values, the KF output waveform is able to optimally reduce internal and process noise so that the output waveform is relatively linear as shown in Figure 12. In this inductive load, disturbance is applied to the DC motor's input supply by providing a PWM value to produce a different duty cycle (D) value. If the D value is increased, the KF output will increase, and vice versa, it will decrease. Although the sensor output value changes over a certain time period, the KF output can still maintain its stability by significantly reducing noise.



(a)



(b)



(c)

Figure 12. Sensor and KF output display with different Duty Cycle (D) (a) D=59, 78, and 59% (b) D= 59, 69, and 55% (c) D= 78, 59, and 78%

3.2.4. Variance of Sensor and KF Output with Difference Duty Cycle (D)

Calculation of sensor and KF output variance on inductive load with different Duty Cycle (D) changes, namely 140, 150, 195, and 200% with R = 100 and Q = 0.1 as shown in Table 4 is intended to determine the effectiveness of using the Kalman filter algorithm if disturbance is given to the Motor DC input. Based on Table 4, it shows that the variance value on KF output at several different D values is much smaller than the sensor output.

Table 4. Sensor and KF output Variances on inductive load.

Duty Cycle D (%)	Sensor Output Variance (A)	KF Output Variance (A)
140	0.3981	0.0011
150	0.3992	0.0013
195	0.3863	0.0130
200	0.01748	0.0011

4. Conclusions

The calculation results show that the variance value of the KF output is much smaller than that of the sensor output, both for resistive and inductive loads. Thus, the KF works effectively on both resistive and inductive loads to improve the accuracy of DC current measurements. The Output of Standard Kalman Filter (KF) which has been implemented with the ESP32 Microcontroller are influenced by the values assigned to the noise sensor covariance matrix (R) and process noise covariance (Q). With a value of R=100, for resistive loads the values of Q=0.5, while for inductive load (DC motor), the values of Q=0.05 can be used optimally. However, the value of the constant Q can be changed depending on the type and size of the load used. The process of determining parameters (Q) in this study employs a trial-and-error methodology by looking at the results of previous research on the Kalman Filter Application [4]. In the future research, it is recommended to use a theoretical approach connected with load characteristics to obtain the optimal Q Constant value for time efficient.

In Most Applications, the use of the INA219 DC sensor obtained from the market place cannot be used directly because the output still contains significant noise both on resistive and inductive loads. Experimental results show that the Standard Kalman Filter (KF) is very suitable for reducing noise in the use of the INA219 sensor. Besides that, the implementation of KF is highly recommended for use in dynamic systems, for example in DC motor control when applying rapid changes to the motor input by changing the Duty Cycle (D) in PWM method, because KF has advantages in its estimation accuracy and is adaptive to rapid changes compared to the use of simple filters.

Abbreviations

KF	Kalman Filter
PWM	Pulse Width Modulation
RSSI	Human Machine Interface
DC	Direct Current
MSE	Mean Square Error
GPIO	General purpose Input Output
I2C	Inter-Integrated Circuit
D	Duty Cycle
PLX-DAQ	Parallax Acquisition

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Author Contributions

Achmad Marzuki: Conceptualization, Formal Analysis, Methodology, Software, Supervision, Writing – original draft, Writing – review & editing

Taufik Muzakkir: Data curation, Formal Analysis, Project administration, Resources, Validation

Muhammad Sulkhan Arief: Data curation, Formal Analysis, Project administration, Resources, Validation

Conflicts of Interest

The authors declare no conflicts of interest.

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